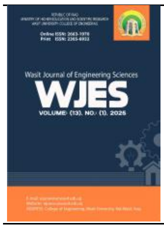

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Review Article

Artificial Intelligence–Driven Smart Home Energy Management Systems: Deep Learning–Based Load Forecasting, Optimization Strategies, and Open Research Challenges

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ABSTRACT

Conventional residential buildings integrated with Artificial Intelligence (AI) and smart home technologies, are transforming into smart, adaptive, and energy-efficient environments. In this review, we discuss current development made in the field of AI-based energy management systems in residential homes. We methodically evaluate and classify 45 peer-reviewed articles from 2019 to 2025 based on the implemented AI methods, specifically, Machine Learning (ML), Deep Learning (DL), Deep Reinforcement Learning (DRL), or hybrid frameworks. The studies reviewed here investigate energy efficiency at the level of HVAC, lighting, and appliances, evaluate their control architectures, deployment strategies, as well as algorithmic design. The reported findings reveal that electricity cost savings, under acceptable thermal comfort can be reached by Multi-Agent Deep Reinforcement Learning (MADRL) systems. However, the literature also Indicate significant hurdles, especially regarding data privacy issues, computational burden, generalization to different buildings, and real-time control viability. In this paper, we propose a hybrid intelligent architecture integrating Proximal Policy Optimization (PPO), Long Short-Term Memory (LSTM) networks, and Graph Neural Networks (GNN) to effectively manage the heating, cooling and lighting components of smart homes for energy efficient management. Furthermore, several approaches in the AI domain are analyzed in order to point out the respective strengths, weaknesses, and future of each in the context of occupant comfort, efficiency, and sustainability in Buildings. The outcomes of this study intend to support researchers, system designers, and decision-makers in advancing robust and scalable AI-enabled smart home energy solutions.

Keywords: Artificial Intelligence; Energy Efficiency; HVAC Systems; Lighting Control.

1. Introduction

Buildings account for a large proportion of the total energy used, since they contribute to a significant percentage of greenhouse gas emissions [1]. This highlights the importance of increasing the energy efficiency of buildings and implementing sustainable design and operation [1]. Energy consumption in buildings breaks down with Heating, Ventilation, and Air Conditioning (HVAC) systems, as the largest energy-consuming sector, exceeding half of the energy used in buildings in developed nations [2]. Alongside HVAC systems, lighting also represents a significant portion of energy consumption in buildings [3]. Due to this, efficient management of these loads plays a critical role in reaching optimal performance and reducing economic and environmental impacts [1, 2]. Smart Homes (SHs) utilize integrated energy management frameworks to improve efficiency while balancing user comfort and operational constraints [3, 4]. Conventional control strategies include Rule-Based Controllers

(RBCs) and Proportional Integral Derivative (PID) controllers. These strategies are primarily based on predefined knowledge from specialist systems, which renders them less adaptive in domestic environments [2]. Moreover, enhanced advanced control models, such as Model Predictive Control (MPC), demand high computational intensity and complex tuning for the thermal dynamics [2, 4]. In this regard, there is an increasing necessity for adaptive intelligent systems. These systems must ensure effective energy management while achieving an optimal trade-off between energy efficiency and user comfort and acceptance [4, 5].

Artificial Intelligence (AI) and Deep Learning (DL) provide a strong foundation for developing models that are both accurate and efficient in processing. AI and DL algorithms can handle large- scale datasets and the non-linear behaviors that occur in building operations [1, 3]. Reinforcement Learning (RL) has proved to be an efficient technique for handling complex dynamic control problems generally, and in the area of HVAC systems in particular, since it reduces the requirement for complete physical models of the processes [2, 5, 6]. More advanced DL methodologies have been effectively applied in real-time energy management, such as HVAC control and load forecasting. This section presents a survey of recent studies in AI- and DL-based energy management. The focus is placed on progressive time series modeling (LSTM) [1, 7], dynamic policy learning algorithms (PPO) [2], and graph-aware methods (GNN) that leverage the interconnected nature of building systems without relying exclusively on traditional physical models [8].

Although AI holds large potential in smart home energy management, there exist scattered, gap-rich studies in the current literature. Most existing works regarding the application of deep reinforcement learning in HVAC control limit themselves to a few algorithms or a problem-specific scenario, without the availability of a systematic assessment procedure [2]. Earlier research usually considered HVAC systems in isolation. Consequently, researcher gave little attention to how multiple systems, such as lighting and window operations, could interact with one another. The Smart Home energy system cannot reach its full optimization potential by failing to take such variables into account [5].

Moreover, the ability of existing AI-based optimization models to adapt and be applied at a larger scale within a system, rather than an isolated system, is still an open area of concern for further research [4]. These issues provide a strong justification for this systematic review, which aims to gather existing knowledge. This review conducts a comprehensive comparison of current AI and ML models for optimizing lighting, heating, ventilation, and air conditioning systems in smart homes, and develops a roadmap addressing existing constraints and future studies in this field [5, 9]. This conceptual framework is summarized in Figure 1.

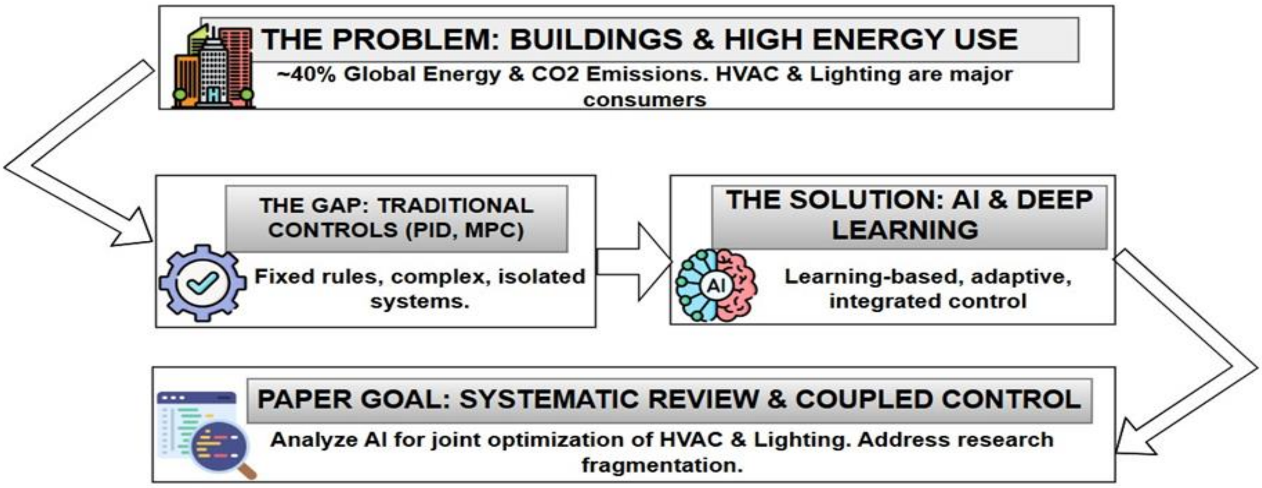

Figure1. A Conceptual Framework from Energy Challenges to AI Solutions

This review examines the role of Artificial Intelligence in reducing smart home energy consumption, focusing on control and optimization strategies for HVAC and lighting system. The structure of this paper is organized as follows: Section 2 introduces Smart Home Energy Management Systems; Section 3 clarifies the role of Artificial Intelligence in energy optimization; Section 4 details literature search strategy and selection process; Section 5 investigates Artificial Intelligence based load forecasting and consumption prediction; Section 6 presents performance evaluations and comparative analyses; Section 7 discusses current challenges and open issues; and finally, Section 8 concludes the paper.

2. Smart Home Energy Management Systems

The Smart Home Energy Management System (SHEMS) is a multi-layer technology to synchronize energy usage, expenditure, and user comfort in an intelligent manner that improves home energy efficiency and its sustainability [10, 11]. It normally consists of four interacting levels- as illustrated in Figure 2- which include the physical level, sensor level, communication level, and management level [12].

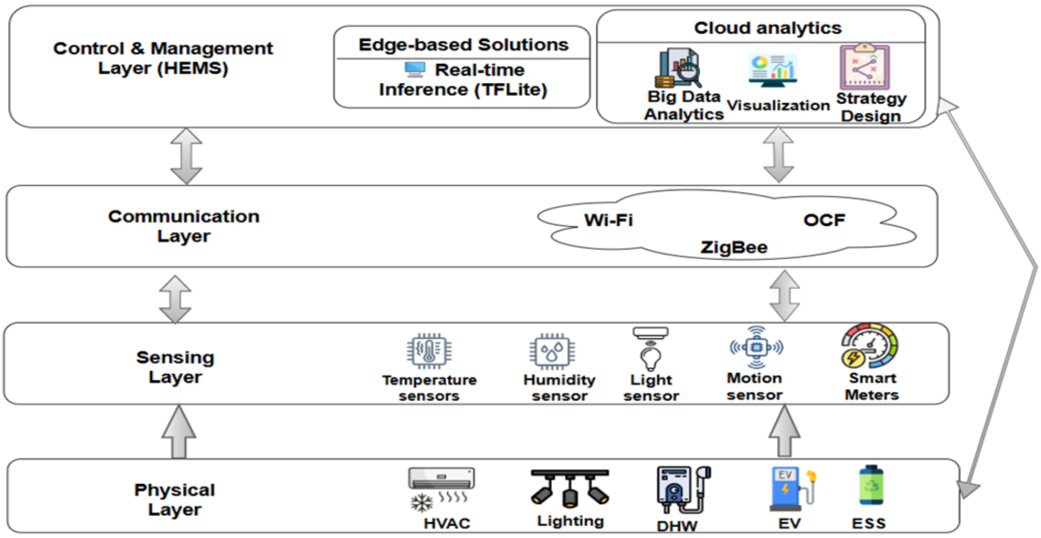

Figure 2. Multi-Layer Architecture of The Smart Home Energy Management System (SHEMS)

The physical layer involves all the energy-consuming loads that act as control objects, and the heating, ventilation, with (HVAC) systems being the primary energy consume [10, 13]. It also includes other loads such as hot water heaters, lighting systems, and intelligent loads including electric vehicles (EV) and energy storage systems (ESS) [10].

The sensing layer comprises intelligent sensors, microcontrollers, and meters, always has the environment in focus, providing information in real-time [12, 14]. Key inputs include environmental conditions (indoor/outdoor temperature, humidity, illumination) [14], occupancy status (presence, movement, and activity levels) [11, 14, 15], and energy metrics (real-time consumption and micro generation from PV panels) [12, 16]. This information determines the system's "state," forming the foundation for predictive analysis and control decisions [16].

This communication layer enables the construction of the structural framework for reliable real-time data transfer from physical components to the control system [14]. This layer utilizes wired technologies such as Ethernet, but Wi-Fi, ZigBee, and LoRa are more widely used in wireless communication in such layers [9]. Among them, it is noteworthy that ZigBee offers maximum power conservation and high security, as it employs 128-bit AES encryption on its communication channel [9, 17]. To address interoperability challenges among devices from different manufacturers—the "IoT fragmentation problem" [12], formalized protocols like the Open Connectivity Foundation (OCF) offer an architectural framework for secure device discovery, resource management, and data communication [12]. Such solutions enable smooth communication within the local area network [14, 18]. In the upper management and control layer, commonly implemented using the Home Energy Management System (HEMS) solution [16], the computational processing of sensor readings is used for the production of intelligent control commands [14]. This layer is established and implemented on IoT platforms with the use of cloud and edge computing solutions for different purposes [12, 19].

- Cloud-based solutions primarily manage long-term data consolidation, large-scale data analysis, user visualization of energy consumption patterns, and strategic decision-making design [20].
- Edge-based solutions (e.g., using embedded devices like Raspberry Pi) [21], are essential for implementing trained models (often converted to lightweight formats like TF Lite) to enable real-time control with low-latency and control closer to the source [12]. Occupant preferences and environmental predictions are combined into the control component to perform predictive optimization [22]. Optimized decisions are then communicated to actuators, such as HVAC and lighting systems, to minimize energy consumption while maintaining thermal comfort [12, 14]. This closed-loop process of sensing, forecasting, and optimization allows AI algorithms to tackle complex and dynamic control challenges effectively.

3. Artificial Intelligence Techniques for Energy Optimization

The application of machine learning and deep learning represents artificial intelligence technology implemented efficient energy management systems in smart homes and buildings. Predictive control approaches aimed at realizing several goals simultaneously, like minimizing costs and maintaining user comfort, have outperformed classical control techniques [23]. These developments have led to the incorporation of machine learning, deep learning, and reinforcement learning into hybrid systems.

3.1. Traditional Machine Learning Approaches

Traditional machine learning methods, especially the supervised ones, are the basis for several early AI-driven applications in energy optimization. Techniques such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and tree-based models like Random Forests (RF) find common applications ranging from energy consumption prediction to system fault classification [23, 24, 25]. ANNs are widely recognized for their ability to model complex nonlinear patterns within large data sets and have been commonly used for performance modeling, load forecasting, and power system optimization [23, 26]. For the same reason, support vector machines have been recognized for their ability to achieve predictive accuracy, especially when dealing with datasets or where there is non-linear data. (SVMs) can also be used for estimation and predictions of the power load to develop accurate prediction systems [23, 26]. An essential advantage in traditional machine learning models like "Decision Trees" and "Random Forests" is that they are interpretable, as the decision-making procedure remains relatively clear [27]. However, an essential weakness in these " shallow " models is that they are less capable or adept at learning from the complex patterns extracted from high-dimensional data streams in contemporary smart home IoT configurations [25]. Conventional approaches are compared below (Table 1).

Table 1. Comparison of Traditional Machine Learning Approaches for Energy Optimization.

Comparison Criterion	ANN	SVM	Decision Trees (DT)	Random Forests (RF)
Performance	Model nonlinear relationships in large datasets	Strong performance with small or nonlinear datasets	Good fault classification; limited generalization with massive data	Improved predictive accuracy; better generalization with massive data
Applications	Energy forecasting, performance modeling, load forecasting, power system optimization	General energy consumption prediction, power load forecasting	System fault classification, troubleshooting	Complex problem classification, failure prediction, self-healing infrastructures
Strengths	Effective with large nonlinear datasets	Robust performance with limited datasets	High interpretability, easy to use	High interpretability, accuracy improved via ensemble learning
Limitations / Challenges	Limited generalization with high-dimensional IoT data	Challenges with massive/high-dimensional data	Limited generalization, potential algorithmic bias	Limited generalization, computational complexity due to ensemble nature

3.2. Deep Learning Models for Load Forecasting and Energy Management

Deep Learning (DL) techniques, as a category of ML, resolve the scalability and complexity constraints that often obstruct standard approaches in various fields [26, 28]. These methods are highly efficient for tasks Dealing with complex data patterns, particularly in load forecasting and predictive analysis [23, 29]. Recurrent Neural Network (RNN) and sophisticated Long Short-Term Memory (LSTM) networks play a significant role in processing sequential data to predict energy consumption and the generated power of renewable sources, such as solar PV, in the proposed system because they yield high accuracy in their prediction capabilities [9, 23]. The LSTM network has long been the most outstanding in time-series analysis due to its ability to remember information from previous steps [23]. Convolutional Neural Networks (CNNs), though originally designed for image processing, have found solid use in energy management. They have excelled in the extraction of meaningful patterns from intricate temporal data, therefore aiding to smooth in noisy signals, and can be employed as a preprocessing component to RNN-based systems [6]. Though accurate and possessing outstanding capabilities to handle nonlinear patterns compared to conventional ML algorithms, the ability of deep learning algorithms requires a robust training dataset. Also, they are challenged by the problem of accumulating errors in the process of recursion in forecasting, especially when the forecast is used in control systems operating in real time [6, 30]

3.3. Reinforcement Learning Methods for Energy Scheduling and Real-Time Control

Reinforcement Learning (RL) provides an appropriate learning paradigm to address complex control and sequential decision-making tasks without requiring the explicit modeling of physical systems [6, 13, 31]. By constantly interacting with the environment, reinforcement learning agents learn optimal control policies through action-and-reward cycles, thus making it suitable for real-time control in HVAC systems [6, 32]. The absence of a model in RL is a highly desirable aspect of the technique over traditional Model Predictive Control (MPC) since the latter is based on the complex development of accurate physical models [2].

Deep Reinforcement Learning (DRL) utilizes deep learning models to address the high dimensional and continuous nature of the state and action spaces that exist in the context of building energy systems [33]. Reinforcement learning algorithms are employed for major operational issues such as real-time control and scheduling to increase energy efficiency and the level of comfort [23]. Deep Q-Networks (DQNs) are appropriate for use in an environment where the action space is discrete and finite [2]. Recent work focuses increasingly on algorithms that manage continuous action spaces such as Deep Deterministic Policy Gradient (DDPG) approaches [10]. This set of continuous-control methods has proven to be very proficient at fine-grained, real-time setpoint regulation, such as temperature and humidity ,without the performance hit which can come from discretizing actions [33]. Controllers based on DRL reduce the costs by 30% in simulated environments compared to the basic strategies. In practical environments, the range of costs that decrease with the implementation of an RL system varies between 11% and 21% on different days while ensuring that the thermal comfort level remains satisfied [32-34]. Although the application of the developed solutions is feasible with current technological capabilities due to the relatively lower complexity of the system deployed on the building's roof, the DRL system is computationally intensive and may take a significant amount of time to train [24].

3.4. Hybrid AI Techniques

However, to sufficiently address more complex and high-dimensional problems related to energy management within the limits set by existing independent modeling, the application of Hybrid AI solutions has proven to be reliable and efficient. Specifically, Multi-Agent Deep Reinforcement Learning (MADRL) provides critical support in managing multi-zone buildings by employing multiple agents to address coupled constraints and strive for system-wide optimal objectives [35]. Evidence has confirmed that MADRL-aided solutions are more effective than single-agent DRL strategies in lowering electricity costs by up to 51.09% compared to conventional rule-based approaches [35].

In efforts to shorten the normally lengthy training times needed for DRL, the TL-DRL enables knowledge transfer from one application, such as network weights, to another, thereby speeding up the rate of convergence [13]. This technique has proven capable of increasing the efficiency of training by an average of 13.28% more than the DRL models with a new training approach [13]. Model-Based Deep Reinforcement Learning belongs to this category as well. its goal is to increase sample efficiency and reduce costs in exploration by using simulation models, which are usually trained using previous data and Energy Plus model [10].

Integration of DL and RL increases efficiency due to synergy gained by taking advantage of the strengths of both methods. DL is excels at recognizing spatiotemporal relationships useful in predicting demands, while RL provides a robust framework for control without a model. Nevertheless, there are several obstacles that have to be addressed, including increased complexity, instability, ambiguities, and simulation-to-reality gap. These technologies and their applications in energy management are shown in Fig. 3

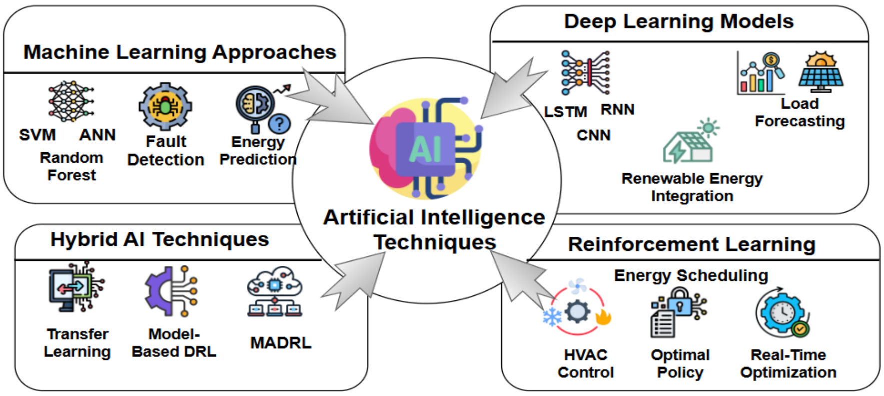

Figure 3. Classification of AI Algorithms For Energy Optimization

4. Literature Search Strategy and Selection Process

A meticulous literature selection process was done in compliance with the PRISMA standards in order to ensure clarity and rigor. The literature selection initially involved carrying out an extensive search in IEEE Explore, Science Direct, Springer Link, and the Web of Science database, which resulted in the collection of 110 records published from 2019 to 2025. The redundant records were removed from the search results, and 98 articles were left that were subjected to screening in terms of their titles and abstracts in the initial phase of the literature selection process; 36 articles were removed after the inclusion or exclusion of criteria. The complete studies of the remaining 62 articles were subsequently assessed for methodological quality and relevance to AI-driven energy optimization in HVAC and lighting systems. A total of 45 high-quality, peer-reviewed studies were retained for the final descriptive and comparative analysis. The process of study selection is presented by using a PRISMA-style horizontal flowchart (Figure 4), which details the four major steps: Identification, Screening, Eligibility, and Inclusion. This flowchart illustrates how the literature was filtered, ensuring transparency and reliability of the review method.

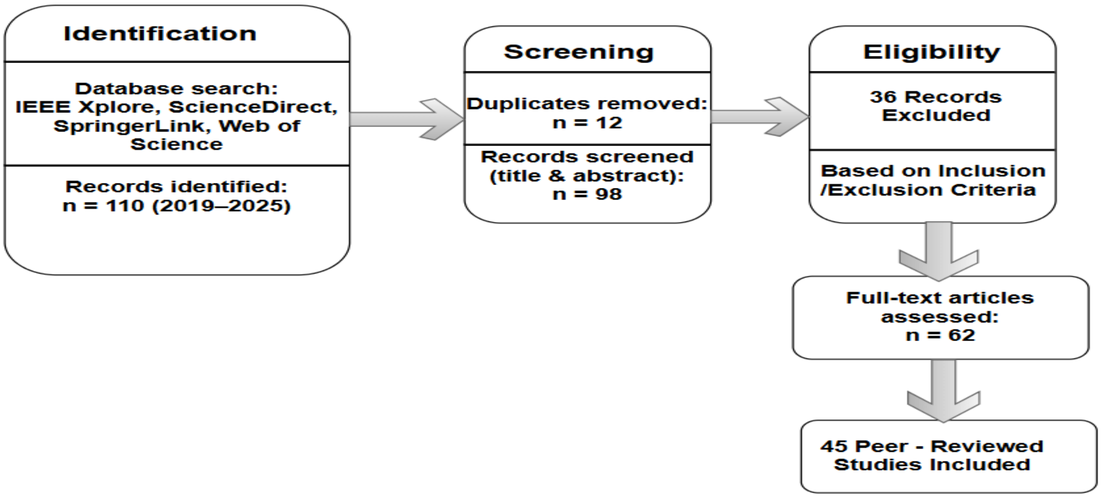

Figure 4: PRISMA-Based Literature Screening Flow Diagram

5. AI-Driven Load Forecasting and Consumption Prediction

5.1. Short- term and long-term energy forecasting

Can use artificial intelligence (AI) and deep learning (DL) algorithms to model complex, non-linear time-series patterns for both short- and long-term energy demand forecasts. The use of short-term forecasts that range from hours to days, as emphasized in the article review referenced as [30], allows real-time control, which helps in maintaining stability and effectively managing resource allotments. On the other hand, the models utilize long-term forecasts that extend beyond several years, which assist in planning and analyzing sustainable patterns over this period by incorporating economic factors and population trends [30]. Deep recurrent neural networks

(RNNs) and long short-term memory (LSTM) networks have proved effective in capturing latent temporal dependencies that naturally exists in multivariate, nonlinear data. The systematic literature review referenced in this document has established this by using data from previous studies, including environmental, occupancy, and equipment usage data [36]. More recent studies combine graph neural networks (GNNs) with deep learning (DL) models to integrate spatial relations in multi-zone systems and nodes in the power system itself with state-of-the-art results through the use of graph data, test cases like the IEEE 30-bus system, and electrical variables to enhance the accuracy of the results and reduce operation expenses [37]. Nonetheless, recursive approaches in the prediction techniques for deep reinforcement learning agents become difficult to apply, which often reduces the accuracy of the results [6].

5.2. Occupant-Centric Control using Occupancy-based Prediction

Occupant-Centric Control (OCC) is based on Multi-Agent Deep Reinforcement Learning (MADRL)—a scenario in which multiple agents collaborate to control energy usage as well as the comfort level of various zones, along with accounting for inter-agent affective factors. Its ultimate objective is to effectively control HVAC systems despite random elements such as human presence, human energy metabolism, as well as changes in clothing. OCC learns to adjust automatically to occupant behavior to ensure thermal comfort and energy efficiency [38, 39]. Recent studies have suggested that multi-agent deep reinforcement learning (MADRL) can reduce energy consumption by over 51% compared to conventional rule-based control, all under the same thermal comfort conditions [35]. Moreover, the hybrid strategy of XGBoost with Deep Q-Network (XGB-DQN) can increase the comfort duration by as much as 24% compared to reference control methods [5].

5.3. Appliance-level energy modeling

In the appliance layer, energy characterization involves developing scheduling methods that reduce the consumption of electricity and decrease the Peak to Average Ratio (PAR). Methods from the Heuristic Optimization Techniques (HOTS) family, such as genetic algorithms and hybrids such as GmPSO, have reported PAR reduction of up to 57.1% when applied to renewable energy systems [4]. More modern developments in Deep Reinforcement Learning (DRL), such as the Soft Actor Critic (SAC) algorithm, have been employed for precise setpoint control, where load adaptation enhances the self-consumption of PV production [2, 16]. However, toward achieving robust smart grid control, notable knowledge gaps still exist, especially in the scalability of models to be more suitable for larger systems, modeling unknown dynamics, as well as concerns about the 'black-box' models of current DL approaches [36]. These forecasting tasks, control levels, and the resulting research gaps are illustrated in Figure 5.

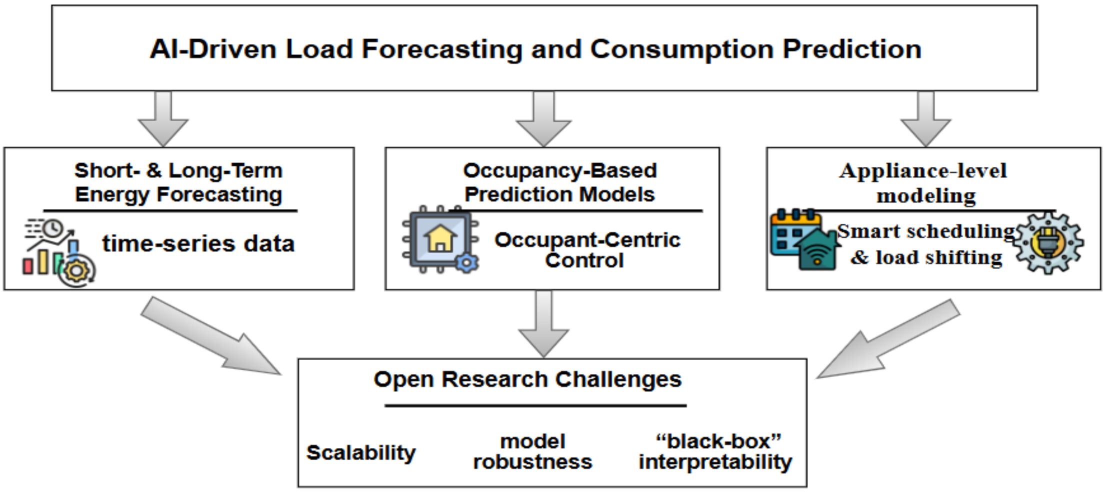

Figure 5. AI-Driven Energy Forecasting and Control Framework

6. Performance Evaluation and Comparative Analysis

6.1. Evaluation Metrics

In order to verify the performance of algorithms for energy management systems in intelligent buildings, a structured performance analysis is essential [40]. Recent studies are focused on multi-dimensional performance evaluation [41]. Metrics used to measure forecast accuracy range from Mean Absolute Error (MAE) to Root

Mean Square Error (RMSE) to Mean Absolute Percentage Error (MAPE) [5, 25]. RMSE is more sensitive to larger errors; however, MAE gives a better direct measure of the average inaccuracy of the forecast [7]. To investigate the load leveling performance, operational parameters including Peak-to-Average Ratio (PAR) are used, subsequently impacting grid reliability [4] .Thermal comfort parameters, such as Predicted Mean Vote (PMV), Predicted Percentage of Dissatisfied (PPD), and the Comfort Compliance Ratio (CCR) are used for maintain indoor thermal environments at acceptable levels [33, 38].

6.2. Comparison of AI Models

Comparing various AI paradigms reveals significant trade-offs between complexity and performance. If we consider conventional machine learning tasks, such as support vector machines and linear regression, it is observed that their speed and efficiency are easier to achieve in the beginning. However, complex processes such as those in thermo-systems, which involve non-linear characteristics and probability patterns, become quite challenging [2, 3]. Conversely, Deep Learning (DL) models, especially Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), enhance time-series forecasting by capturing long-range temporal relationships more effectively and reducing issues such as gradient instability problems [12, 15]. For active control, various recent works have been using the Deep Reinforcement Learning (DRL) methods comprising Soft Actor-Critic (SAC), Proximal Policy Optimization (PPO), and Deep Q-Networks (DQN). These methods learn the optimal control policy by directly interacting with the environment without using any detailed physical model [2, 5].

6.3. Energy Savings and System Efficiency

AI-based energy management systems significantly improve efficiency, yielding energy and cost savings between 15% and 51% [32, 40]. In particular, multi-agent deep reinforcement learning (MADRL) environments have already indicated cost savings of up to 51.09% compared to rule-based baseline methods [35], as well as around 42.31% with WDQN-temPER hybrid systems [25]. To address scalability, the recent studies have utilized Transfer Learning-enabled DRL (TL-DRL), which improves training efficiency by 13.28% by leveraging pre-trained control policies to solve new environments [13]. The comparison of all these performance metrics is shown in (Table 2).

Table 2. Comparison of Representative AI-Driven Energy Management Studies

Study Reference	AI Model Used	Application Domain	Evaluation Metrics	Key Performance Outcomes
35	MADRL (multi-Agent)	Multi-zone Office HVAC	Electricity Cost, PMV, PPD	51.09% cost reduction while maintaining thermal comfort
6	SAC + LSTM	Smart HVAC Operations	Energy Consumption, PMV, RMSE	17.4% energy saving; 16.9% improvement in PMV
12	WOA + LSTM + GRU	Smart Home Optimization	Energy Cost, PMV, MSE	35.98%–38.22% reduction in energy costs
32	DRL (Pre trained)	Residential HVAC	Energy Cost, Comfort	21%–30% cost reduction in real and simulated houses
38	DQN	Multi-VAV Open Office	Energy Consumption, Temperature Violation	37% energy reduction with <1% temperature violation
4	GmPSO (Hybrid)	Smart Home Load Scheduling	PAR, Energy Cost, CO_2 Emissions	57.1% PAR reduction; 40% cost savings
16	DRL	Home Heating & DHW	Energy Savings, Comfort	8%–16% energy savings with <1% discomfort

This Study	PPO + LSTM + GNN (Hybrid)	Smart Home HVAC, Lighting, and Appliances	Energy Cost, Energy Consumption, Thermal Comfort (PMV), RMSE	Proposed hybrid framework for coordinated control and energy efficiency

7. Challenges and Open Research Issues

AI-driven management of energy in smart buildings has several challenges related to data privacy and security, owing to the increased usage details of the building's occupants that need to be collected, thus increasing concerns of cyber security and privacy breaches [39, 42]. Moreover, the complexity of the building architecture and the high computation required in the process of training the deep learning (DL) models pose significant difficulties since requires increased computational power, which in turn contributes to carbon emissions [41, 43]. Further, the implementation and development of such models are impeded by the black-box nature of neural networks and the lack of standardized datasets. This leads to imprecise interpretation and generalization of control policies in other buildings and in different climate zones [22, 44]. In view of these challenges, the demand for efficient algorithms with explain ability, and the ability to achieve strong performances without spending heavily to modify the present systems, is well underlined [14, 45].

8. Conclusion

The significance of this review paper is to discuss the transformative impact of Artificial Intelligence (AI) in enhancing energy efficiency and comfort in smart domestic settings. Based on a comprehensive literature study of 45 technical papers from well-established journals and conferences, AI-driven strategies involving machine learning (ML), deep learning (DL), deep reinforcement learning (DRL), and hybrid techniques have consistently outperformed traditional rule-based systems in HVAC systems, lighting systems, and appliance-level systems. Though there has been significant progress in terms of energy efficiency development and efficiency of process, there are still remaining constraints remain to be addressed. These pertain to the challenges posed to AI-driven models regarding issues of data privacy, model complexity, scalability, and real-time deployment limitations. The future course of this subject should focus on the development of more explainable AI-driven models that are flexible enough to meet the previously identified challenges while maintaining the level of user comfort. The method being proposed for this study entails the creation of a hybrid intelligent model that utilizes Proximal Policy Optimization, Long Short-Term Memory, and Graph Neural Network architectures for energy optimization in smart homes. The goal is to optimize energy use while ensuring maximum convenience for users, by considering the spatiotemporal aspect of thermal dynamics.

Declaration of Competing Interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

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Author Contributions

All authors contributed to proposing the research problem. Faisal Theyab Abed. oversaw the general research framework, provided scientific guidance, and reviewed the technical aspects of the study. Jamal Saad A.Omer and Rania Ragab Hussein reviewed the manuscript and offered critical feedback to enhance its quality. Roaa A.Mohammed developed the methodology, carried out the comparison , analysis and prepared the manuscript. All authors reviewed and approved the final version.

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